

ENAE 441 - 0101
HW03: System Propagation

Due on October 30th. 2025 at 09:30 AM

Dr. Martin, 09:30 AM

Vai Srivastava

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Problem 1: Propagation Functions (30 pts.)

Please implement the following functions in your code to confirm your understanding of the different propagation strategies. You are not required to use these exact functions in subsequent questions, as there may be more appropriate / efficient implementations for subsequent questions. They are merely provided as a way to confirm your own understanding of the process.

- Write a function that propagates a LTI system forward numerically¹ and plot the displacement $x(t)$ and velocity $\dot{x}(t)$.
- Write a function that propagates a LTI system forward analytically using a continuous time (CT) STM².
- Write a function that propagates a LTI system forward analytically using a discrete time (DT) STM³.
- Write a function that propagates a LTV system by jointly integrates the nominal trajectory and the state transition matrix for a fixed amount of time⁴.
- Write a function that returns the maximum allowable sampling time for a discrete time system to avoid aliasing.

Solution

Part A

```

122 # REQUIRED --- 1a
123 def propagate_CT_LTI_numerically(X_0, X_dot_fcn, t_vec):
124     t0 = float(t_vec[0])
125     tf = float(t_vec[-1])
126
127     reversed_time = tf < t0
128     if reversed_time:
129         t_eval = np.asarray(t_vec[::-1])
130         t_span = (float(t_eval[0]), float(t_eval[-1]))
131     else:
132         t_eval = np.asarray(t_vec)
133         t_span = (t0, tf)
134
135     sol = solve_ivp(
136         fun=X_dot_fcn,
137         t_span=t_span,
138         y0=np.asarray(X_0).reshape(-1),
139         t_eval=t_eval,
140         rtol=1e-9,
141         atol=1e-12,
142         vectorized=False,

```

¹using Python's `scipy.integrate.solve_ivp`

²Be sure to use `scipy.linalg.expm` to make the matrix exponential

³Be sure to use `numpy.linalg.matrix_power` to raise the matrix to a power

⁴Hint: Form a joint state-STM vector $\mathbf{z} = [\mathbf{x}_{\text{nom}}(t) \quad \phi(t, t_0)]^T$. Unroll the STM into a single column vector such that the object passed to `solve_ivp` is a single column vector. Use $\Phi(t_0, t_0) = \mathcal{I}_{6 \times 6}$ for the initial condition

```

143     )
144
145     if not sol.success:
146         raise RuntimeError(f"solve_ivp failed: {sol.message}")
147
148     X_t = sol.y.T
149     if reversed_time:
150         X_t = X_t[::-1]
151
152     # Return trajectory over time where np.shape(X_t) = (len(t_vec), len(X_0))
153     return X_t

```

Part B

```

156 # REQUIRED --- 1b
157 def propagate_CT_LTI_analytically(X_0, A, t_vec):
158     X_0 = np.asarray(X_0).reshape(-1)
159     A = np.asarray(A)
160     t_vec = np.asarray(t_vec)
161     t0 = float(t_vec[0])
162
163     X_t = np.empty((len(t_vec), len(X_0)), dtype=float)
164     for i, t in enumerate(t_vec):
165         Phi = expm(A * (float(t) - t0))
166         X_t[i] = Phi @ X_0
167
168     # Return trajectory over time where np.shape(X_t) = (len(t_vec), len(X_0))
169     return X_t

```

Part C

```

172 # REQUIRED --- 1c
173 def propagate_DT_LTI_analytically(X_0, A, dt, k_max):
174     X_0 = np.asarray(X_0).reshape(-1)
175     A = np.asarray(A)
176     A_d = expm(A * float(dt))
177
178     n = X_0.size
179     X_t = np.empty((int(k_max) + 1, n), dtype=float)
180
181     # x[0]
182     X_t[0] = X_0
183
184     # x[k] = A_d^k x[0]
185     # (explicitly use matrix_power as the assignment requests)
186     for k in range(1, int(k_max) + 1):
187         A_dk = np.linalg.matrix_power(A_d, k)
188         X_t[k] = A_dk @ X_0

```

```

189
190     # Return trajectory over time where np.shape(X_t) = (len(t_vec), len(X_0))
191     return X_t

```

Part D

```

194 # REQUIRED --- 1d
195 def propagate_LTV_system_numerically(X_0, x_dot_fcn, A_fcn, t_vec):
196     n = len(X_0)
197     phi0 = np.eye(n).flatten()
198     z0 = np.hstack((X_0, phi0))
199
200     def z_dot(t, z):
201         x = z[:n]
202         phi = z[n:].reshape((n, n))
203
204         x_dot = x_dot_fcn(t, x)
205         A_t = A_fcn(x)
206         phi_dot = A_t @ phi
207
208         return np.hstack((x_dot, phi_dot.flatten()))
209
210     sol = solve_ivp(z_dot, [t_vec[0], t_vec[-1]], z0, t_eval=t_vec)
211
212     X_t_vec = sol.y[:n, :].T
213     phi_t_vec = np.zeros((len(t_vec), n, n))
214     for i in range(len(t_vec)):
215         phi_t_vec[i] = sol.y[n:, i].reshape((n, n))
216
217     # Return trajectory and STM over time where
218     # np.shape(X_t_vec) = (len(t_vec), len(X_0))
219     # np.shape(phi_t_vec) = (len(t_vec), len(X_0), len(X_0))
220
221     return X_t_vec, phi_t_vec

```

Part E

```

1 0.7853981633974481

```

Code

See the [Python code](#) for this assignment.

Problem 2: Continuous Time Linear System (30 pts.)

Consider a spring-mass-damper system

$$m \ddot{x}(t) + c \dot{x}(t) + k x(t) = 0$$

with system mass $m = 1$, damping coefficient $c = 0.5 \frac{\text{Ns}}{\text{m}}$, and spring constant $k = 4 \frac{\text{N}}{\text{m}}$ and an initial condition of $\mathbf{x}(0) = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$.

The system is measured by observing the position

$$y(t) = x(t)$$

- Express the system as a continuous-time state-space model and as a discrete-time model. Define a state vector of $\mathbf{x}(t) = \begin{bmatrix} x(t) \\ \dot{x}(t) \end{bmatrix}$ and define all of the corresponding matrices. Assume no external input ($\mathbf{u}(t) = 0$).
- Propagate the system forward for 10 seconds using all three LTI propagation methods and plot $x(t)$ and $\dot{x}(t)$ on the same figure.
- Compare the results. What happens when you apply a Δt value that exceeds the critical threshold in the DT STM?
- Use the set of position measurements in `HW3-spring-data.npy` to determine the initial state $\mathbf{X}(t=0)$ for a different trajectory.
- How many measurements are needed to ensure the state $\mathbf{x}(t)$ is observable if $\Delta t = 1$ s? Explain your findings.

Solution

Part A

With state $\mathbf{x}(t) = \begin{bmatrix} x(t) \\ \dot{x}(t) \end{bmatrix}$ and output $y(t) = x(t)$, the continuous-time model is

$$\dot{\mathbf{x}}(t) = \mathbf{A}\mathbf{x}(t), \quad \mathbf{A} = \begin{bmatrix} 0 & 1 \\ -\frac{k}{m} & -\frac{c}{m} \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ -4 & -0.5 \end{bmatrix}, \quad \mathbf{C} = \begin{bmatrix} 1 & 0 \end{bmatrix}, \quad \mathbf{D} = \mathbf{0}$$

For a sampling period Δt , the discrete-time model (no input) is

$$\mathbf{x}_{k+1} = \mathbf{A}_d \mathbf{x}_k, \quad y_k = \mathbf{C} \mathbf{x}_k,$$

with $\mathbf{A}_d = e^{\mathbf{A}\Delta t} = \Phi(\Delta t)$

Because this is a 2nd-order underdamped oscillator, it's convenient to write $\alpha = \frac{c}{2m} = \frac{1}{4}$, $\omega_n = \sqrt{k/m} = 2$,

and $\omega_d = \omega_n \sqrt{1 - \zeta^2} = 2\sqrt{1 - \left(\frac{c}{2m\omega_n}\right)^2} = 1.98431348$.

The continuous-time STM is

$$\Phi(t) = e^{-\alpha t} \begin{bmatrix} \cos(\omega_d t) + \frac{\alpha}{\omega_d} \sin(\omega_d t) & \frac{1}{\omega_d} \sin(\omega_d t) \\ -\frac{\omega_n^2}{\omega_d} \sin(\omega_d t) & \cos(\omega_d t) - \frac{\alpha}{\omega_d} \sin(\omega_d t) \end{bmatrix}$$

Hence the discrete state matrix is $\mathbf{A}_d = \Phi(\Delta t)$ with the same $\alpha, \omega_n, \omega_d$ substituted, and $\mathbf{C}_d = \mathbf{C}, \mathbf{D}_d = \mathbf{D} = \mathbf{0}$

Part B

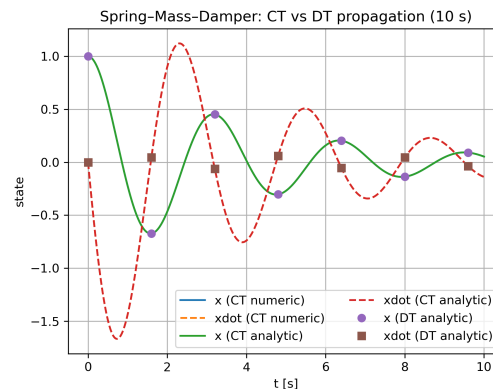


Figure 1: Propagation Trajectories

Part C

Comparison:

- CT numerical (solve_ivp) integrates $\dot{x} = A x$ and returns $x(t)$ at requested t .
 - ↳ Accuracy depends on tolerances;
 - ↳ it handles stiff/ill-conditioned cases with adaptive steps.
- CT analytic uses the continuous-time STM $\Phi(t, t_0) = \expm(A (t-t_0))$, giving the exact state
 - ↳ at any t for LTI systems.
- DT analytic samples the exact CT solution at multiples of Δt by forming $A_d = \expm(A \Delta t)$
 - ↳ and $x[k] = A_d^k x[0]$.
 - ↳ At the sample instants, this is mathematically identical to CT analytic.

Critical sampling:

Let $\lambda = \sigma \pm j \omega_d$ be complex poles and $\omega_n = |\lambda|$ the undamped natural frequency. The Nyquist bound is

$$\Delta t_{\max} = \pi / \max \omega_n.$$

For this system, $\max \omega_n = 2$ rad/s $\Rightarrow \Delta t_{\max} = \pi/2 \approx 1.5708$ s.

What happens if $\Delta t > \Delta t_{\max}$?

- The discrete-time eigenangle is $\theta = \omega_d \Delta t$. Angles are wrapped modulo 2π in discrete time,
 - ↳ producing an aliased apparent frequency $\omega_{\text{alias}} = |\omega_d - 2\pi/\Delta t \cdot \text{round}(\omega_d \Delta t / 2\pi)|$.
- The DT trajectory $x[k] = A_d^k x[0]$ is still the exact CT solution *at those sample instants*, but if you attempt to infer the underlying oscillation from samples (or connect samples with lines), you will
 - ↳ see a lower, incorrect frequency (and possibly sign flips when $\theta \approx \pi$). Estimation and identification tasks will misinterpret the dynamics.
- Stability is preserved here because $|e^{\lambda \Delta t}| = e^{\sigma \Delta t} < 1$ ($\sigma < 0$), but phase is
 - ↳ misrepresented beyond Nyquist.

Part D

```

1 [[2.99911711]
2  [1.69178453]]

```

Part E

```

1
2 2 measurements (e.g., at k=0 and k=1 with Δt=1 s) are sufficient.
3 Reason: the 2×2 observability matrix O2 = [ C ; C Ad ] equals
4   [[1, 0],
5    [φ11(Δt), φ12(Δt)]],
6 which has full rank iff φ12(Δt) ≠ 0. For this system,
7   φ12(Δt) = e-α Δt · (1/ωd) · sin(ωd Δt),
8 and with α=0.25, ωd≈1.9843 rad/s, Δt=1 s ⇒ sin(ωd Δt) ≠ 0, so rank(O2)=2.
9 Thus the discrete-time state is observable from two consecutive position measurements.

```

Code

See the [Python code](#) for this assignment.

Problem 3: Continuous Time Non-Linear System (40 pts.)

Consider a satellite in a 3D Keplerian orbit around Earth. The dynamics of the satellite can be modeled using Newton's second law under the gravitational force:

$$\ddot{\mathbf{r}} = -\frac{\mu}{r^3}\mathbf{r},$$

where $\mu = 398\,600 \frac{\text{km}^3}{\text{s}^2}$ is the Earth's gravitational parameter and \mathbf{r} is the position vector of the satellite in the Earth-centered inertial (ECI) frame.

The initial position and velocity vectors are:

$${}^{\mathcal{N}}\mathbf{X}(0) = \begin{bmatrix} 7000 \text{ km} \\ 0.0 \text{ km} \\ 0.0 \text{ km} \\ 0.0 \frac{\text{km}}{\text{s}} \\ 7.5 \frac{\text{km}}{\text{s}} \\ 3.5 \frac{\text{km}}{\text{s}} \end{bmatrix}^{\top}$$

and the measurement function of the system is the range, ρ taken from an observer at $\phi = 30^\circ$ latitude and $\lambda = 60^\circ$ longitude, where the radius of the Earth, R_E is taken as 6378 km and the rotation of the Earth is $\omega_{E/N} = 7.292\,115\,0 \times 10^{-5} \frac{\text{rad}}{\text{s}}$. Define the state vector as $\mathbf{x}(t) = [\mathbf{r}(t) \quad \mathbf{v}(t)]^{\top}$.

- Linearize the system around a nominal trajectory $\mathbf{X}_{\text{nom}}(t)$, deriving the system and output matrices $A = \frac{\partial \mathbf{f}}{\partial \mathbf{x}}$ and $C = \frac{\partial \mathbf{h}}{\partial \mathbf{x}}$.
- Write a function that outputs A_k .
- Write a function that outputs C_k .
- Numerically propagate (i) the nominal trajectory and (ii) the nominal trajectory perturbed an initial state deviation of $\delta\mathbf{X} = [30, 0, 0, 0, 0, 0.1]^{\top}$ for 90 minutes. Plot the difference in the position vector $\delta r(t)$ as a function of time.
- Propagate the state deviation directly using the integrated state transition matrix from the augmented nominal state vector (i.e. [here](#)) and plot the position vector deviation as a function of time.
- Increase the initial state perturbation to $\delta\mathbf{X} = [1000, 0, 0, 0, 0, 0.1]^{\top}$ and integrate (i) numerically and (ii) using the STM. Plot $\delta r(t)$ for both propagation strategies.
- Explain what you see.
- A set of range measurements are provided for a different trajectory in `HW3-kepler-data.npy` from the same observer. Use the measurements to estimate the initial state deviation $\delta\mathbf{x}(t_0)$ using the same nominal trajectory as before.
- Explain your approach.

Solution

Part A

State: $\mathbf{x} = [\mathbf{r}; \mathbf{v}] \in \mathbb{R}^6$, dynamics

$$\dot{\mathbf{x}} = \begin{bmatrix} \dot{\mathbf{r}} \\ \dot{\mathbf{v}} \end{bmatrix} = \begin{bmatrix} \mathbf{v} \\ -\frac{\mu}{\|\mathbf{r}\|^3}\mathbf{r} \end{bmatrix} =: f(\mathbf{x})$$

Let $r = \|\mathbf{r}\|$. The Jacobian is

$$\mathbf{A} = \frac{\partial f}{\partial \mathbf{x}} = \begin{bmatrix} \mathbf{0}_{3 \times 3} & \mathbf{I}_{3 \times 3} \\ \mu \left(\frac{3\mathbf{r}\mathbf{r}^\top}{r^5} - \frac{\mathbf{I}_{3 \times 3}}{r^3} \right) & \mathbf{0}_{3 \times 3} \end{bmatrix}$$

Measurement: range to a ground observer $\rho = \|\mathbf{r} - \mathbf{r}_{\text{obs}}(\mathbf{t})\|$

Hence

$$\mathbf{C} = \frac{\partial \rho}{\partial \mathbf{x}} = \begin{bmatrix} \frac{(r - r_{\text{obs}}(t))^\top}{\|r - r_{\text{obs}}(t)\|} & \mathbf{0}_{1 \times 3} \end{bmatrix}$$

The observer position in ECI (with latitude ϕ , longitude λ , Earth radius R_E , rotation rate ω_E) is

$$\mathbf{r}_{\text{obs}}^{\text{ECI}}(t) = \mathbf{R}_3(\omega_E t) \begin{bmatrix} R_E \cos(\phi) \cos(\lambda) \\ R_E \cos(\phi) \sin(\lambda) \\ R_E \sin(\phi) \end{bmatrix}, \quad \mathbf{R}_3(\theta) = \begin{bmatrix} \cos(\theta) & -\sin(\theta) & 0 \\ \sin(\theta) & \cos(\theta) & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Part B

```

1 | [[ 0.00000000e+00  0.00000000e+00  0.00000000e+00  1.00000000e+00
2 |    0.00000000e+00  0.00000000e+00]
3 | [ 0.00000000e+00  0.00000000e+00  0.00000000e+00  0.00000000e+00
4 |    1.00000000e+00  0.00000000e+00]
5 | [ 0.00000000e+00  0.00000000e+00  0.00000000e+00  0.00000000e+00
6 |    0.00000000e+00  1.00000000e+00]
7 | [ 2.32419825e-06  0.00000000e+00  0.00000000e+00  0.00000000e+00
8 |    0.00000000e+00  0.00000000e+00]
9 | [ 0.00000000e+00 -1.16209913e-06  0.00000000e+00  0.00000000e+00
10 |    0.00000000e+00  0.00000000e+00]
11 | [ 0.00000000e+00  0.00000000e+00 -1.16209913e-06  0.00000000e+00
12 |    0.00000000e+00  0.00000000e+00]]

```

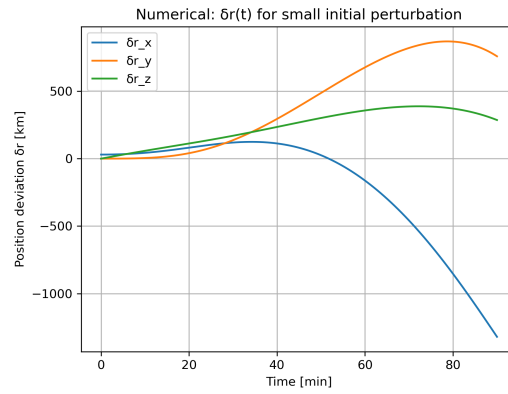
Part C

```

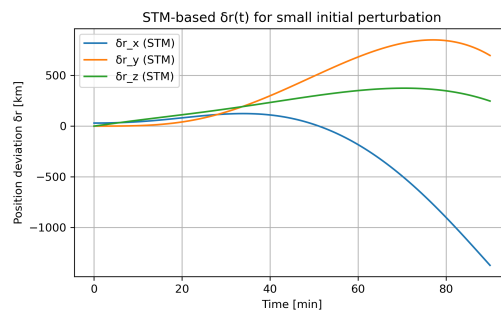
1 | [[ 0.59338974 -0.66973    -0.44648667  0.          0.          0.          ]]

```

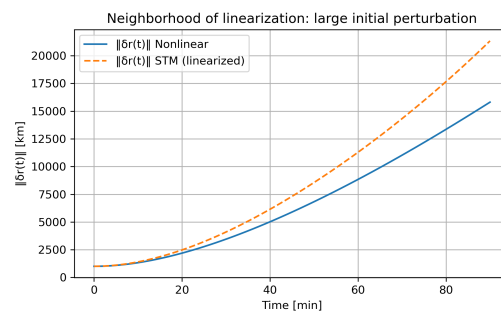
Part D

Figure 2: Numerical Integration $d\mathbf{X}$

Part E

Figure 3: Analytic Integration $d\mathbf{X}$

Part F

Figure 4: Critical $d\mathbf{X}_{\text{neighborhood}}$

Part G

```

1 | For small perturbations, the STM linearization matches the nonlinear  $\delta r(t)$  closely: the
2 | direction and amplitude agree because the first-order model captures the local flow and
   |  $\hookrightarrow$  gravity-gradient
3 | coupling along the nominal path. When the initial deviation is increased, higher-order terms
   |  $\hookrightarrow$  (curvature of
4 | the vector field and coupling through  $1/\|r\|^3$ ) become significant over an orbital timescale.
   |  $\hookrightarrow$  The STM keeps
5 | projecting the initial deviation through  $\Phi(t, t_0)$  built on the nominal, so its prediction
   |  $\hookrightarrow$  grows biased: phase
6 | drifts and amplitude errors accumulate, especially near perigee where the field is most
   |  $\hookrightarrow$  nonlinear.
7 | The plot shows divergence in  $\| \delta r(t) \|$ : nonlinear truth departs from the linear prediction,
   |  $\hookrightarrow$  evidencing the
8 | finite neighborhood of validity for the first-order model.

```

Part H

```

1 | [ 7.38541948e+04  4.50585150e+06 -6.94356932e+06 -1.32578732e+03
2 | -1.42889210e+03  3.01612462e+03]

```

Part I

```

1 | We linearize the range model about the nominal:  $y_k = p(r_k)$  with  $r_k \approx r_{\text{nom},k} + \delta r_k$ ,
2 |  $\delta X_k = \Phi_k \delta X_0$ . The measurement Jacobian is  $C_k = [ (r_{\text{nom},k} - r_{\text{obs},k})^T / p_{\text{nom},k},$ 
   |  $\hookrightarrow 0_{\{1 \times 3\}} ]$ .
3 | Thus  $y_k - p_{\text{nom},k} \approx (C_k \Phi_k) \delta X_0$ . Stacking all samples yields a linear least-squares
   |  $\hookrightarrow$  problem:
4 |  $\min_{\delta X_0} \| y_{\text{res}} - H \delta X_0 \|_2$ , where rows of  $H$  are  $C_k \Phi_k$ . We integrate once along the
   |  $\hookrightarrow$  nominal
5 | and its STM to get  $X_{\text{nom}}(t_k)$ ,  $\Phi_k$ , build  $H$  and the residual vector  $y_{\text{res}}$ , then solve with
6 |  $\text{np.linalg.lstsq}$ . This provides the best linearized estimate of the initial deviation  $\delta X_0$ 
   |  $\hookrightarrow$  given
7 | range-only data and the chosen nominal trajectory.

```

Code

See the [Python code](#) for this assignment.